Otto-von-Guericke-University Magdeburg
Faculty of Computer Science

Master's Degree Thesis Proposal

Automated Aneurysm Centerline Extraction using Deep Learning: A Point Cloud-based Approach

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List of Acronyms

AI Artificial Intelligence

IA Intracranial Aneurysms

AAA Abdominal Aortic Aneurysms

TAA Thoracic Aortic Aneurysms

CT Computed Tomograph

MRI Magnetic Resonance Imaging

EVAR Endovascular Aneurysm Repair

DL Deep Learning

CAD Computer-Aided Diagnosis

CNN Convolutional neural network

MRA Magnetic Resonance Angiogram

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1 Introduction

1.1 Background and Motivation

An estimated 6.8 million people in the United States have an unruptured brain aneurysm, or 1 in 50 people. Aortic aneurysm deaths increased in number between 1990 and 2019 in a global burden of disease analysis (94,968 to 172,427). The global burden of death attributable to aortic aneurysms began to increase after decreasing for two decades [1]. There are almost 500,000 deaths worldwide each year caused by brain aneurysms, and half the victims are younger than 50. [2]

Intracranial Aneurysms (IAs) remain a significant public health issue, with a prevalence of up to 3.2% [3]. Incidentally detected aneurysms are becoming more common due to the availability and increasing quality of non-invasive imaging techniques [3].

An aneurysm is a bulging, weakened area in the wall of a blood vessel resulting in an abnormal widening or ballooning greater than 50% of the vessel's normal diameter (width) [4] as shown in Figure 1.1

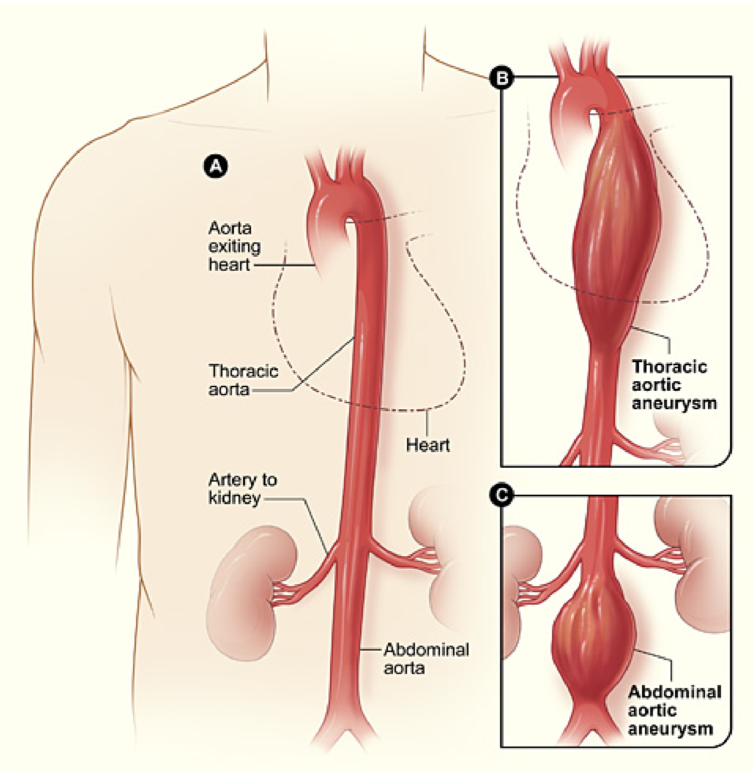

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Figure 1.1: Normal aorta (A), thoracic aortic aneurysm (B) and abdominal aortic aneurysm (C). Aortic aneurysm. [5]

An aneurysm can be located in many areas of the body such as aorta, legs, brain, neck, etc but most common sites are aorta and brain. An aortic aneurysm occurs when there is a weakening in the wall of the aorta, which then bulges outwards due to pressure of blood flowing through it. Aortic aneurysms, particularly Abdominal Aortic Aneurysms (AAAs) and Thoracic Aortic Aneurysms (TAAs), are serious conditions characterized by the weakening and bulging of the aortic wall. AAAs typically occur in the lower part of the aorta, while TAAs affect the upper part near the heart. Brain aneurysms, also known as cerebral aneurysms or intracranial aneurysms, are abnormal bulges or ballooning in blood vessels within the brain. [6] [7] [8]

Aneurysm can lead to various complications depending on its location. It can lead to :

- Rupture: Aneurysms can burst or rupture, leading to severe internal bleeding, which can be life-threatening. [9]
- Thromboembolism: A clot may form in the aneurysm and break loose, traveling through the bloodstream and potentially causing blockages in other parts of the body. [10]
- Pressure effects: Aneurysms can put pressure on surrounding tissues or organs, leading to symptoms related to compression. [3]
- Hydrocephalus: In cases of subarachnoid hemorrhage from a ruptured brain aneurysm, acute hydrocephalus (build-up of fluid in the brain) can occur. [3]

An aneurysm may be caused by multiple factors that result in the breaking down of the well-organized structural components (proteins) of the aortic wall that provide support and stabilize the wall. Atherosclerosis (hardening of the arteries with a sticky substance called plaque) is thought to play an important role in aneurysmal disease. Some of the risk factors associated with it includes older age, family history, genetic factors, hyperlipidemia (elevated fats and cholesterol in the blood), hypertension,trauma, smoking, diabetes , obesity, poor diet, inactive lifestyle. [11]

Aneurysms may be asymptomatic (no symptoms) or symptomatic (with symptoms). Symptoms associated with aneurysms depend on the location of the aneurysm in the body. Symptoms will depend on whether an aneurysm has ruptured or not. Symptoms that may occur with different types of aneurysms may include, but are not limited to:

- Abdominal Aortic Aneurysm (AAA): Constant pain in abdomen, chest, lower back, or groin area. [12]
- Cerebral Aneurysm: Sudden severe headache, nausea, vomiting, visual disturbance, loss of consciousness, loss of vision. [9]

- Femoral and Popliteal Artery Aneurysm: Easily palpated (felt) pulsation of the artery located in the groin area (femoral artery) or on the back of the knee (popliteal artery), pain in the leg, sores on the feet or lower legs. [10]

The selection of a type of diagnostic examination is related to the location of the aneurysm. In addition to a analysis of complete medical history, various tests can be performed. Diagnosis of a ruptured cerebral aneurysm is commonly made by finding signs of subarachnoid hemorrhage on a Computed Tomography (CT) scan. If the CT scan is negative but a ruptured aneurysm is still suspected based on clinical findings, a lumbar puncture can be performed to detect blood in the cerebrospinal fluid. Computed tomography angiography (CTA) is an alternative to traditional angiography and can be performed without the need for arterial catheterization. This test combines a regular CT scan with a contrast dye injected into a vein. Once the dye is injected into a vein, it travels to the cerebral arteries, and images are created using a CT scan. These images show exactly how blood flows into the brain arteries. There are other various tests that can be performed such as ultrasound, echo, Magnetic Resonance Imaging(MRI), and many more depending on the need of moment. [13] [14] [15]

Specific treatment will be provided by the doctor depending on the age, medical history, location and size of aneurysm, symptoms, and overall health of the patient. There are various treatment options such as:

- Routine ultrasound procedure: These procedures will monitor the size and rate of growth of the aneurysm every 6 months to 12 months as part of a watchful waiting approach for smaller aneurysms. [16]

- Controlling lifestyle: Steps such as quitting smoking, controlling blood sugar if diabetic, losing weight if overweight or obese, and controlling dietary fat intake may help to control the progression of the aneurysm. [4]

- Medication: Medication can control factors such as hyperlipidemia (elevated levels of fats and cholesterol in the blood) and/or high blood pressure. [14]

- Open repair surgery: An incision is made to directly visualize and repair the aneurysm. A cylinder-like tube called a graft may be used to repair the aneurysm. This graft is sewn to the involved blood vessel, connecting 1 end of the artery at the site of the aneurysm to the other end. The open repair is considered the surgical standard for an abdominal aortic aneurysm repair. [16]

- Endovascular Aneurysm Repair (EVAR): EVAR is a procedure that requires only small incisions in the groin along with the use of X-ray guidance and specially-designed instruments to repair the aneurysm. [16]

The diagnosis methods mentioned earlier are highly dependent on well-trained radiologists for the interpretation of the images for the ultimate diagnostic reports. Since the screening for aneurysm is mostly done by MRI or CT imaging, the aneurysms are detected via visual assessment of the scans, which is a cumbersome task subject to human error. The accuracy and time taken for interpretation depend on the expertise of the radiologists; thus, inconsistent diagnostic outcomes are often produced.

Studying aneurysm in the medical field is essential to improve the understanding of the underlying causes and risk factors associated with aneurysm formation by which we can develop methods for early detection. It also allows development of more effective treatment options and helps in improving patient outcomes and reducing healthcare costs.

Various aneurysms are common nowadays and how to detect them intelligently is of great significance in digital health. A high efficiency and detection sensitivity can be achieved or even improved using computer-assisted deep learning and artificial intelligence-based approaches. Considering the challenges faced in the detection and management of aneurysm, Artificial Intelligence (AI) techniques have been developed to automatically interpret complex data, drawing correlations that will ultimately enhance precise detection of aneurysms and inform the best decisions on their management.

In this thesis, we will be focusing on the development of a robust and accurate centerline extraction method for the detection and analysis of aneurysms. I will be working on PointNET [17] deep learning approach for centerline extraction in my thesis. The results of this research could contribute to better understanding the risk factors and underlying causes associated with aneurysm formation, as well as aid in the development of more effective treatment options, thereby reducing healthcare costs and improving patient outcomes.

1.2 Research Question

Can a deep learning model based on PointNET accurately predict the centerline of a 3D aneurysm surface mesh, and how does it perform compare to traditional methods?

2 Literature Review

To understand the motivation behind this thesis, it is worth looking into what contributions have been made so far in this field. Over the decade many researchers have proposed different methods to detect, locate and segment aneurysm. This section will explore various aspects of already proposed research and its benefit, drawbacks and potential research gap.

With the integration of computer intelligence technology and medical imaging technology, Deep Learning (DL) has become a hot research topic in the field of Computer-Aided Diagnosis (CAD) in recent years [18]. It is useful in medical image detection, classification, segmentation, alignment, image retrieval, image generation, and image enhancement. Deep learning can help doctors and the common features of disease diagnosis from the big data of medical images and provide scientific methods for disease screening and treatment in clinical medicine.

2.1 Previous Research

Studies have shown that [19] compared with manually annoted 2D planar images, 3D morphological analysis for computer-aided diagnosis improves the accuracy and consistency of parameter measurement and also quantifies shape irregularities more reliably. Research conducted on 2D MRA images has been confined to 3D neural networks that operate on pixels and voxels, overlooking the manifold's information.This issue can be addressed by developing neural networks that can capture and utilize the overall structure or "manifold" of the image along with the individual pixel and voxel information. This could involve designing algorithms that are capable of understanding the relationships between different parts of the image and incorporating this understanding into the network's architecture.

In recent years, many researchers have applied deep learning algorithm to aneurysm detection and measurement to assist physicians in detecting lesions before they rupture [20]. Stember [21] first used convolutional neural networks to automatically detect cerebral aneurysms from MRA and successfully detected 85 of 86 test set aneurysms; second, the u-net network was used to predict the size of 14 basilar aneurysms, with results that differed from radiologist-labeled aneurysms by an average size of 2.01 mm and an average area of 8.1 mm^2. Daju [22] used a ResNet-18 structured neural network for automatic detection of aneurysms on TOF-MR angiography images. To detect aneurysms that were overlooked in the initial report, two radiologists were blinded to the algorithm's detection results. The results showed that the algorithm improved the detection of aneurysms in the internal and external test sets by 4.8% and 13% respectively over the original data set. Sichterman [23] used the CNN-based DeepMedic framework for aneurysm detection on 3D TOF-MRA images with datasets collected from different magnetic elds as well as different hospitals and showed that the algorithm has a sensitivity of 96% for aneurysms of 3–7 mm. In summary, almost all existing work focuses on medical images rather than 3D geometric point clouds.

While existing deep learning algorithms have shown promising results in aneurysm detection and measurement using medical images, there is still a need to explore alternative data representations that can provide more accurate and comprehensive information about aneurysm geometry. Point clouds, which represent 3D geometric data as a set of unordered points, offer several advantages over traditional medical images. Firstly, point clouds can capture the intricate and irregular shapes of aneurysms more accurately than voxel-based representations. This is because point clouds can represent the surface of an aneurysm with a higher resolution, allowing for more precise measurements and analysis. [17]

Secondly, point clouds can provide a more complete representation of aneurysm geometry, including the centerline, which is a critical feature for understanding aneurysm morphology and hemodynamics [24]. Centerline extraction plays a crucial role in aneurysm analysis as it aids in identifying the central path of blood vessels, which is essential for various medical applications such as surgical planning and treatment assessment. The need to study centerline extraction techniques lies in their ability to provide accurate vessel morphology information, facilitate aneurysm localization, and enable precise measurements for treatment planning. Understanding centerline extraction methods is vital as it enhances the accuracy and efficiency of aneurysm diagnosis and treatment through automated processes that reduce manual intervention and improve diagnostic outcomes. To extract the centerline from point clouds, we can use deep learning algorithms such as PointNet, which is a pioneering neural network architecture for processing point clouds. PointNet can directly consume point clouds as input and learn features that are invariant to permutations of the input points [17].

By using PointNet for centerline extraction, we want to achieve more accuracy and consistent results compared to traditional methods. In Chapter 3, we will be discussing more about PointNET architecture in brief.

3 Methodology

In this chapter, we will explore deep learning architecture capable of reasoning about 3D geometric data such as point clouds or meshes. PointNET [17] proposed by Charles R. Q is the origin of point cloud learning. This type of learning can directly process the point cloud by learning the corresponding spatial encoding for each point in the input point cloud and then using the features of all points to obtain a global point cloud feature, ignoring the local relations of geometric shapes.

3.1 Overview of PointNet

PointNet is a powerful deep learning algorithm that excels at processing point cloud data, making it ideal for tasks like centerline extraction in complex structures such as arteries. The architecture for PointNet is shown below:

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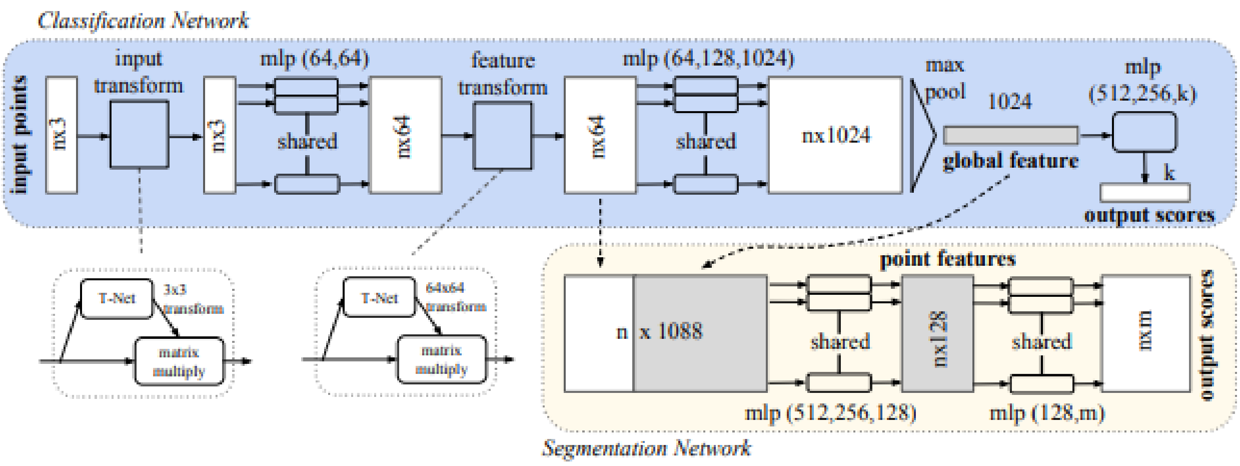

Figure 3.1: PointNet Architecture

The classification network takes n points as input, applies input and feature transformations, and then aggregates point features by max pooling. The output is classification scores for k classes. The segmentation network is an extension to the classification net. It concatenates global and local features and outputs per point scores. “mlp” stands for multi-layer perceptron, numbers in bracket are layer sizes. Batchnorm is used for all layers with ReLU. Dropout layers are used for the last mlp in classification net.

3.2 Dataset

I am provided with a dataset of 50 meshes and its centerline. The 3D surface meshes and its centerline are in the format of .obj and .dat respectively. The 3D meshes and centerline are extracted from MRI DICOM image using a pipeline proposed by L.Spitz [25].VMTK is a collection of libraries and tools for 3D reconstruction, geometric analysis,mesh generation and surface data analysis for image-based modelling of blood vessels The overview of pipeline is shown below:

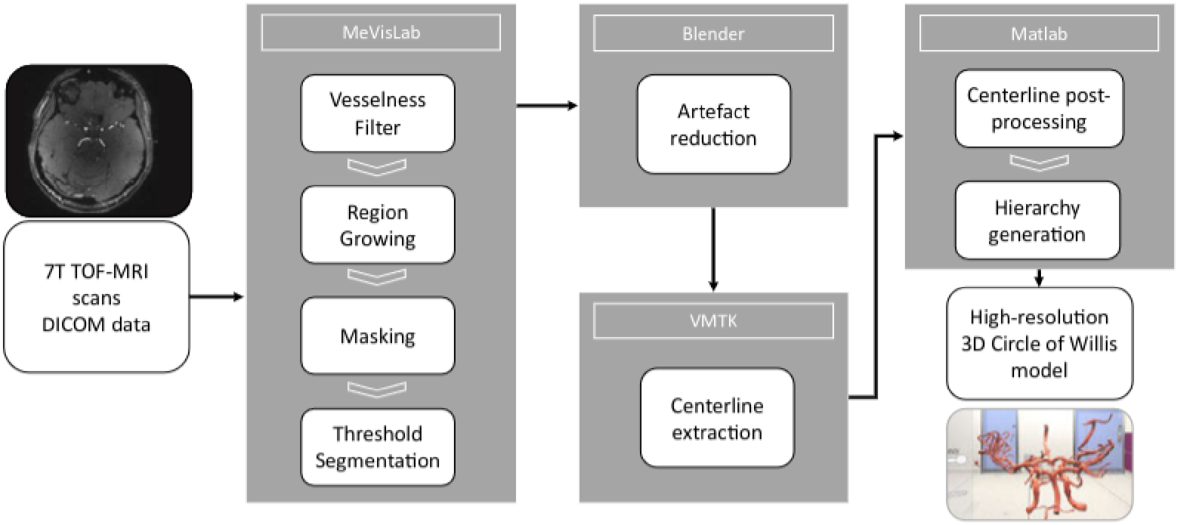

Figure 3.2: Pipeline for mesh and centerline extraction [25]

3.3 Data preparation and steps involved

I have 3D surface mesh data (.obj) and its centerline data (.dat). Organize the mesh and centerline data into a folder, ensuring each pair of files share the same name with different extensions. I am going to use Python programming language.

To convert the 3D surface mesh data into a point cloud, I utilized the Python library called "trimesh" [26]. Trimesh is used for its capability to load, manipulate, and analyze 3D mesh data efficiently. This is necessary as the PointNet model requires the input data to be in the form of a point cloud. After this step we will have a point cloud in 3D space. Each point in the point cloud will have (x,y,z) coordinates.

After generating the point cloud from the mesh data, we incorporate the centerline points into the point cloud dataset. The centerline represents a path or axis through the object, often used for anatomical or structural analysis. It consists of a series of points in 3D space. Each centerline point is added to the point cloud dataset as a separate point with its own coordinates (x, y, z). This step ensures that the centerline is included in the point cloud dataset for subsequent classification.

Next step is to classify points in the point clouds based on their proximity to centerline points using a KD (K-dimensional) tree. This step involves determining the closest points in the point cloud to each centerline point and classifying them accordingly. A KD Tree is a data structure used for efficient nearest neighbor search in multidimensional space. It's particularly useful when dealing with datasets containing points in higher-dimensional spaces, such as 3D point clouds [27]. In KD tree, the distance between points is commonly calculated using the Euclidean distance formula, especially in applications involving spatial data such as point clouds. The Euclidean distance formula computes the straight-line distance between two points in Euclidean space, which is the most intuitive measure of distance in 3D space

The Euclidean distance between two points $P_1(x_1, y_1, z_1)$ and $P_2(x_2, y_2, z_2)$ in 3D space is given by:

$$\text{Distance} = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2 + (z_2 - z_1)^2}$$

I will locate the nearest points to each centerline point (colored red) and classify them as either ID1 (colored green) if they are close or ID2 (colored blue) if they are far away from the red points.

The next step is to define a PointNET model architecture using PyTorch which is a deep learning framework commonly used for building neural network models [28]. Split the dataset into training and testing sets. Most common split of training and testing dataset is 80:20. The 80:20 ratio strikes a balance between having sufficient data for training the model and having a sizable testing set for evaluation. In addition to a train-test split, techniques such as k-fold cross-validation can be used to further assess model performance. Cross-validation involves splitting the dataset into multiple folds and training the model on different combinations of training and validation sets, providing more reliable performance estimates. I created data loaders for efficient loading of data during training, and then train your PointNet model using the training data. Using the ground truth, I trained my model using PointNET architecture on this dataset. The model should learn to predict the centerline for a new 3D aneurysm surface mesh.

During training, you use a CrossEntropyLoss as your loss function and an optimizer (SGD) to update the model parameters iteratively. A loss function, also known as a cost function or objective function, measures how well a machine learning model's predictions match the actual target values during training [29].Cross-Entropy Loss is widely used in classification tasks due to its suitability, differentiability, numerical stability, interpretability, and compatibility with one-hot encoded labels.

After training, I evaluated model's performance using the testing dataset. I calculated metrics such as accuracy, precision, and F1 score to assess the model's classification performance. These metrics provide insights into how well your model is performing in terms of correctly classifying points in the point cloud. Confusion matrix will be used to evaluate the accuracy of the network, where each point is classified as either a centerline point or not, and then compared with the ground truth.

Accuracy measures the proportion of correctly classified instances out of the total number of instances. It provides an overall assessment of the model's performance.

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \times 100 \tag{3.1}$$

Precision measures the proportion of true positive predictions out of all positive predictions made by the model. It indicates the model's ability to avoid false positive predictions.

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \tag{3.2}$$

The F1 score is the harmonic mean of precision and recall, providing a balanced measure of a model's performance. It considers both false positives and false negatives.

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3.3}$$

Confusion matrix provides a detailed breakdown of the model's performance by showing the counts of true positive, true negative, false positive, and false negative predictions.The confusion matrix complements these metrics by providing insights into the types of errors made by the model, such as false positives and false negatives.

Finally, I demonstrated how to use my trained model to classify points in new 3D surface mesh data. I loaded the new data, preprocessed it into a format suitable for input to the model, and then used the trained model to predict the classifications of points in the new data.

The block diagram illustrates in Fig 3.3 the overall process of converting a 3D mesh into a point cloud, classifying centerline points, training a PointNet model, and evaluating the model's performance.

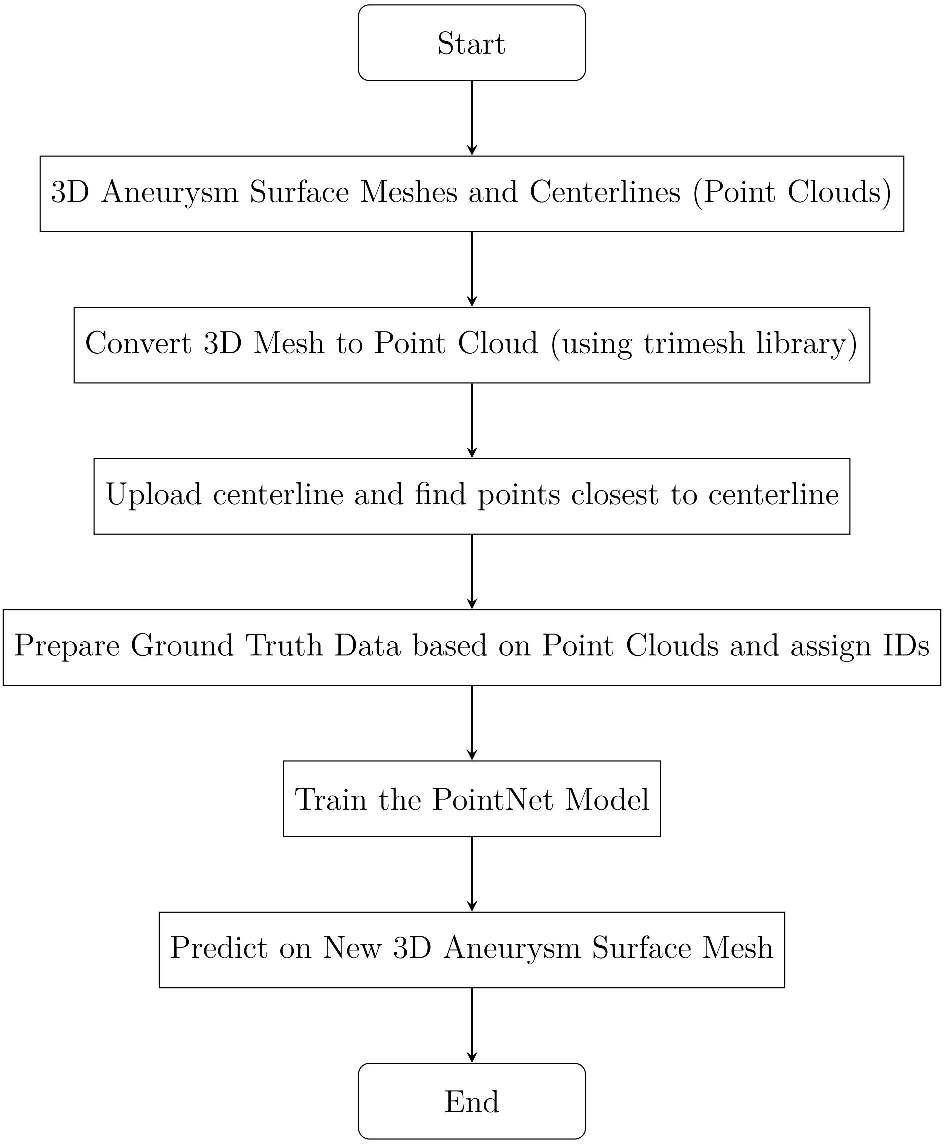

Figure 3.3: Overview of methodology

4 Results

Following the completion of training and testing phases, I have the following results:
Epoch 1, Loss: 0.5094386339187622
Epoch 2, Loss: 0.41916388273239136
Epoch 3, Loss: 0.4466613531112671
Epoch 4, Loss: 0.5339298248291016
Epoch 5, Loss: 0.47125276923179626
Epoch 6, Loss: 0.5322883129119873
Epoch 7, Loss: 0.4106689393520355
Epoch 8, Loss: 0.4410099387168884
Epoch 9, Loss: 0.4421493411064148
Epoch 10, Loss: 0.5022695660591125
Epoch 11, Loss: 0.44106003642082214
Epoch 12, Loss: 0.471338152885437
Epoch 13, Loss: 0.3780752122402191
Epoch 14, Loss: 0.624961793422699
Epoch 15, Loss: 0.37844109535217285
Epoch 16, Loss: 0.5012837052345276
Epoch 17, Loss: 0.3470028340816498
Epoch 18, Loss: 0.5006423592567444
Epoch 19, Loss: 0.5001938343048096
Epoch 20, Loss: 0.5017116665840149

Accuracy: Measures overall correctness of predictions.
Accuracy: 0.841
Precision: Focuses on the accuracy of positive predictions.
Precision: 0.707
F1 Score: Harmonic mean of precision and recall, balancing both metrics.
F1 Score: 0.768

These results indicate that the model's performance is not as strong as the previous example, with an accuracy of 84.1%, precision of 70.73%, and F1 score of 76.84%. It's important to note that this model may have underfitted or overfitted the dataset. To improve the performance, I should adjust the model's architecture, optimizer, learning rate, or training data.

For a better understanding of the model's performance, I should apply data augmentation technique to have diverse dataset and try to run the network with more dataset and to improve the performance of the model.

In general, to determine if your model is underfitting or overfitting, I should compare the training and validation dataset, analyze the learning curve, and observe the model's complexity. Since I don't have any validation set, my next step should be introducing validation set. Validation performance is measured during the training process to assess how well the model generalizes to new, unseen data.

By comparing the training and validation performance, I can get insights into the model's ability to generalize to new data. This will also help me to determine if the model is underfitting, well-fit, or overfitting.

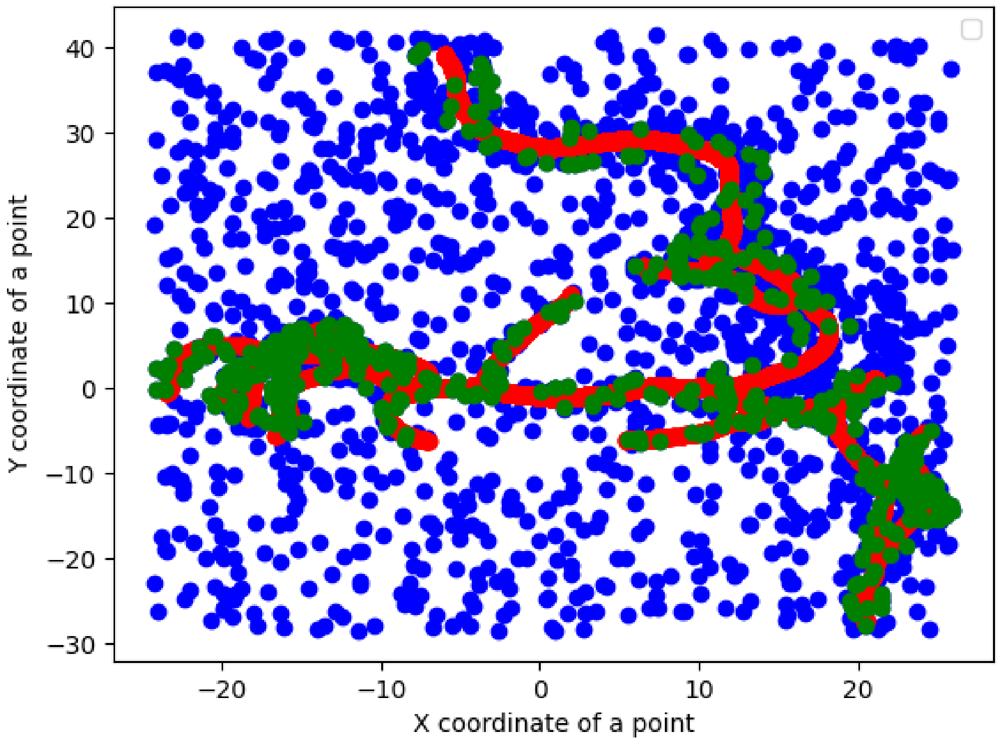

Figure 4.1: Point cloud classification results after training the PointNet model. Red points correspond to the centerline points, while blue points represent points further away from the centerline. Green points are near to the centerline points.

5 Conclusion

The conclusion chapter is where you interpret and explain the results you presented, acknowledge the limitations of your study, provide a Take-Away Message: and future research.

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A Project Proposal

B Appendix

B.1 Python Program